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Article

Evaluation of the climate change impacts and Floodplain restoration in the Kelani River basin, Sri Lanka: a hydraulic modelling approach

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Abstract: The Kelani River basin (KRB) is the highest flooding conditions appeared river basin in Sri Lanka. Based on this, the study investigates the impact of climate resilience on rainfall patterns, temperature, wind speed, and streamflow dynamics of the Kelani River basin in Sri Lanka to enhance flood risk prediction and floodplain restoration planning. Rainfall, temperature, and wind speed data for the 2013 to 2024 time period were obtained from five stations: Angoda, Colombo, Hanwella, Maliboda, and Rathnapura. Long-term trends were detected using statistical approaches such as the Mann-Kendall test. Actual versus predicted streamflow data were used to determine the effectiveness of the hydrological model, along with error distribution analysis. There was some variation in the rainfall; Rathnapura peaked at 6000 mm in 2019, and Maliboda was almost constant throughout. Statistical tests indicated an increase of 3.12 mm per year in rainfall. Within the temperature trends, there was no long-term variation at the Colombo and Rathnapura stations, while in wind speed, a moderate decline without statistical significance was recorded. The hydrological model showed shortcomings in the streamflow forecast, mainly due to underestimating the high flows and overestimating the low flows. The residual analysis indicated a deficiency in the model's representation of extreme events, and the Q-Q plot indicated poor performance in predicting runoff extremes. These limitations highlight the need for model refinement using nonlinear-learning-based approaches to improve flood risk assessment and inform adaptive restoration strategies under changing climate conditions.

Keywords: Rainfall variability; Hydraulic models; Streamflow prediction; Climate variability; Flood restoration

1. Introduction

The significance of accurate weather forecasts cannot be overstated in a rapidly changing environment. Timely and accurate weather forecasts play a crucial role in reducing people's vulnerability to the impacts of extreme weather events. Protecting lives and livelihoods from these events underscores the importance of providing reliable weather forecasts. The changing precipitation patterns are causing more evaporation from reservoirs and lakes, leading to increased rainfall in some areas and reduced rainfall in others (Grover, 2015). As global temperatures increase and precipitation patterns undergo alterations, numerous communities will encounter diminished water resources. The major impacts of climate change are the increasing frequency and intensity of floods and droughts (Van Vliet et al., 2011). Rainfall timing variation and distribution, coupled with escalating water pollution, are exerting pressure on ecosystems, imperiling numerous aquatic and terrestrial species.

Sri Lanka's tropical climate and monsoon-driven rainfall are shaped by patterns from the Bay of Bengal, and a 2018 Global Climate Risk Index assessment named Sri Lanka as one of the ten countries affected by climatic changes (Weerasekara et al., 2021). Sri Lanka's tropical climate is shaped by four

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main monsoon seasons, which bring heavy rains and frequent flooding (Warnasooriya et al., 2022). Sri Lanka has 103 river basins and five major rivers (Mahaweli, Kelani, Kalu, Ging, Nilwala) that flood annually, producing various flood types such as riverine, flash, and coastal floods (Perera, 2021). Sri Lanka's Kelani River basin faces increasing flood risks due to higher flood frequency, flat lower basins, heavy rainfall, and inadequate drainage, with Colombo as a major vulnerable hub (Alahacoon and Edirisinghe, 2021). Among the vulnerable areas, the Kelani River Basin stands out, experiencing large-scale flooding approximately every two to three years, affecting around 200,000 individuals (Samarasinghe et al., 2022). This study aims to evaluate how climate change could alter flood risk in the Kelani Basin by analyzing changes in rainfall intensity and associated hydrological dynamics, using models like HEC-RAS (Rangari et al., 2019). Built in RStudio to simulate river flow, flood discharge, and floodplain interactions, and by examining rainfall, river flow, and floodplain landscapes to assess potential benefits of floodplain restoration as an adaptation strategy, along with the economic and social impacts on communities and policy recommendations for integrating floodplain restoration with urban planning to enhance resilience, while acknowledging concerns about shifting rainfall patterns and ecosystem stability.

This study aimed to assess variation in climate change impacts on hydrological dynamics in the KRB using rainfall patterns, surface temperature trends, humidity, and wind speed variations, and to evaluate the effectiveness of floodplain restoration. The study was integrated by combining statical multi-parameters climate trend analysis with residual diagnostic evaluation of linear regression hydraulic modeling. Specifically, the study analyzed historical rainfall and temperature data to identify long-term climate trends. It assesses expected changes in rainfall patterns, temperature trends, humidity, and wind speed in the basin, develops and implements a hydrological model to simulate climate-change impacts, evaluates potential climate-change–driven impacts on flood risk considering rainfall intensity, river flow, and floodplain inundation, and provides recommendations for sustainable floodplain management based on the findings.

2. Methodology

2.1. Study Area

This study was conducted using data on rainfall, temperature, humidity, and wind speed in the lower basin of the Kelani River (KRB), which flows through the Western and Sabaragamuwa provinces. The KRB is situated between 6° 47' and 7° 05' North latitude and 79° 52' and 80° 13' East longitude in an area of 2230 km in the wet zone, and the altitude ranges from above mean sea level to over 2300 m (Mahagamage and Manage, 2018; Surasinghe et al., 2019). The distribution of annual rainfall in the watershed ranges from 500 to 5,000 mm, with an average of about 3,450 mm. Data were collected from five meteorological and agrometeorological stations in the Kelani lower basin for this study. These are Colombo, Angoda, Hanwella, Maliboda, and Ratnapura stations (Table 1) shows the Longitude, Latitude, and elevation of the weather stations.

Table 1. Selected stations of Lower Kelani River Basin (Department of Meteorology, 2025)

Station	Longitude (°E)	Latitude (° N)	Elevation (m)
Angoda	79.9270	6.9367	15
Colombo	79.8612	6.9271	7
Hanwella	80.0814	6.8978	16
Maliboda	80.4396	6.8906	274
Rathnapura	80.3847	6.7056	86

According to data from the Central Environment Authority, about 2840 factories causing environmental pollution have been reported (Garba and Udokpoh, 2023). The study area of the Kelani River is the main drinking water source in Colombo. Also, the study site is selected under the steep elevation from the upper catchment at (Maliboda/Rathnapura) to the flat lower basin (Angoda/Colombo), creating complex hydrological dynamics ideal for testing a climate resilience model. Likewise, the industrial effluent water from the factories in the BEPZ (Biyagama Export Processing Zone) is released into the Kelani River through the Ambatale and Rakgahwatta canals after treatment. These factors create conflict between urban development and industrial expansion, as in the site, land use across the basin is diverse; the upper and mid catchment area is dominated by tea plantations, rubber, coconut, and paddy cultivation, while the lower basin is heavily urbanized and industrialized (Surasinghe et al., 2019) (Figure 1).

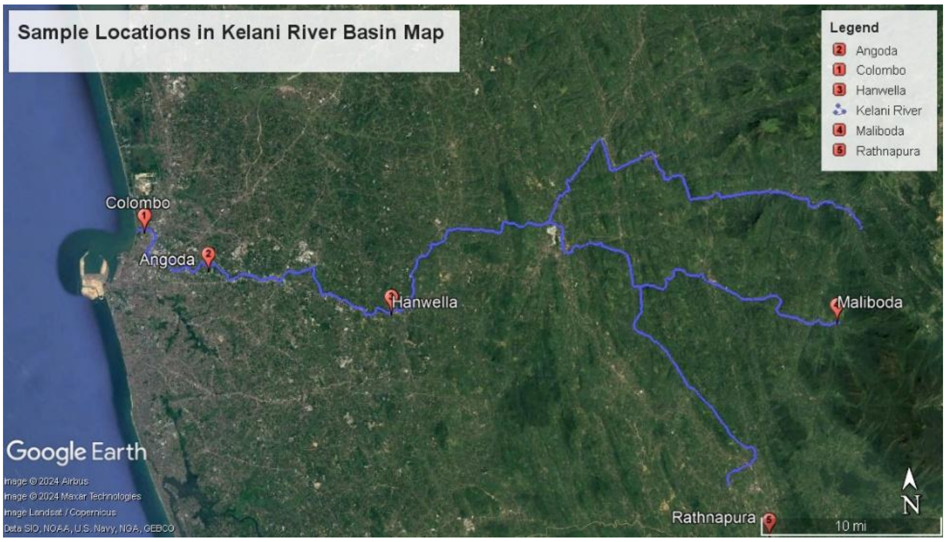


Figure 1. Selected stations in the Kelani River basin in Google Earth Pro

2.2. Collection of Secondary Data and Preparation of Data

The KRB receives rainfall from the Southwest monsoon, Northeast monsoon, and Inter-monsoon. For this study, daily rainfall and temperature data were collected, and monthly historical climate data for the Kelani River Basin were collected. Daily rainfall data, temperature data, and monthly humidity and wind speed data were collected from the Sri Lankan Meteorological Department over 10 years (2014-2024). The daily data were separated into 10 years using Microsoft Excel for five stations.

2.3. Using RStudio for Data Import and Preprocessing

A trend analysis was performed to analyze the data thus prepared. Also, data were calculated separately for Southwest and Northeast seasonal monsoons. Two methods were used for that. The output was obtained by coding (Perera, 2021). A special package called g-plot was used for that. Also, Mann-Kendall and Sen's slope methods were used as statistical methods. P values and Z values for the statistical method of the Mann-Kendall method were calculated using RStudio software (Garba and Udokpoh, 2023). In addition, Sen's slope method was used by calculating the slope value to determine the direction of the rainfall pattern.

$$S = \sum_{i=1}^{n-1} n \sum_{j=i+1}^{n} sgn\left(x_j - x_i\right) \tag{1}$$

Were,

$$sgn\left(x_j - x_i\right) = \{+1, if\left(x_j - x_i\right) > 0, \quad 0, if\left(x_j - x_i\right) = 0 \quad . \quad -1, if\left(x_j - x_i\right) < 0\}$$

Here,

(1) \(n\) represents the total number of data points in the time series.

(2) \(x_i \) and \(x_j \) are the data values at time points \(i\) and \(j\), respectively.

(3) \(\text{sgn}(x_j - x_i)\) is the sign function:

(4) If \(x_j - x_i > 0\), \(\text{sgn}(x_j - x_i) = 1\).

(5) If \(x_j - x_i = 0\), \(\text{sgn}(x_j - x_i) = 0\).

(6) If \(x_j - x_i < 0\), \(\text{sgn}(x_j - x_i) = -1\) (Garba and Udokpoh, 2023).

The variance of S , VAR(S), was calculated as follows,

$$V(s) = \frac{1}{18}[n(n-1)(2n+5) - \sum_{p=1}^{q} t_p(t_p - 1)(2t_p + 5)] \tag{2}$$

Where,
$$Z_{MK} = \{\frac{s-1}{V(s)}, if\ s > 0,$$
$$0, if\ s = 0,\ .$$
$$\frac{s-1}{V(s)}, if\ s < 0\}$$

To calculate Sen's slope method, the calculation was done using Eq.3.

$$T_i = \frac{x_j - x_i}{j - i} \qquad (3)$$

Where,
$$For\ i = 1, \ldots, N$$
$$Q_i = \{T_{\frac{N+1}{2}},\ if\ N\ is\ odd$$
$$T_{\frac{N}{2}} + T_{\frac{N+2}{2}},\ if\ N\ is\ even\}\ .$$

Here,

(1) (T_i) represents Sen's slope estimator for a given data point (*i*).

(a) (x_i) and (x_j) are the data values at time points (*i*) and (*j*), respectively.

(b) (*j*) and (*i*) represent the indices of the data points.

(c)The numerator ((x_j - x_i)) calculates the difference in data values.

(d) The denominator ((*j*-*i*)) represents the time interval between the data points.

(2) The variable (Q_i) depends on whether the total number of data points (*N*) is odd or even:

(a) If (*N*) is odd, then (Q_i = T_{\frac{N+1}{2}}).

(b) If (*N*) is even, then (Q_i = \frac{T_{\frac{N}{2}} + T_{\frac{N}{2} +1}}{2}).

(3) (Q_i) is used in further calculations related to trend analysis (Garba and Udokpoh, 2023).

2.4. Development of Hydrological Model

The hydrological model was developed using historical streamflow, discharge, and weather data from past years to predict flood events in the lower Kelani River basin. Rather than a machine learning approach, standard hydraulic flow modeling built using R in RStudio was utilized for this purpose. The dataset was divided into a 70% subset for model training and calibration and a 30% subset for testing and validation (Riche et al., 2024). The training data was used to build the model, and the test data was used to validate its predictive performance. The physical software, like HEC-RAS, a conventional tool in basin modelling, and the R-based hydraulic and statistical framework were applied for direct streamflow diagnostic analysis. Based on the residual diagnostic findings, integrating a machine learning algorithm is recommended as a future enhancement to further refine predictive accuracy.

2.5. Report findings and document the entire process

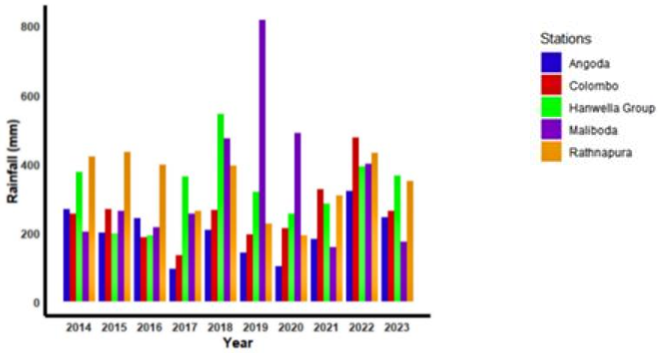
Findings from RStudio were integrated with hydrological modelling to determine the dynamics of climate trends in the KRB and presented using tables, figures, and a constructed map to communicate the findings efficiently.

3. Results and Discussion

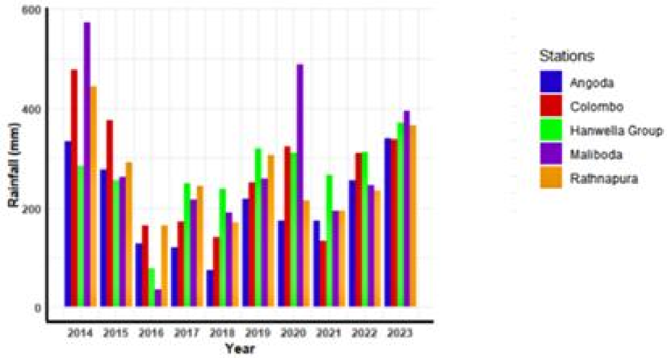
3.1. Rainfall analysis in the Kelani River Flood Plain

This study was conducted based on data on rainfall, temperature, humidity, and wind speed in the lower basin of the Kelani River. Data on historical precipitation, temperature, humidity, and wind speed over 10 years (2014 - 2024) were used to analyze long-term trends in climate change.

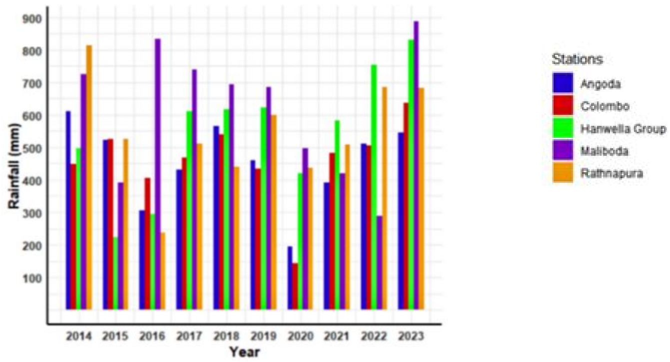
Based on Figure 2, an examination of rainfall patterns during specific monsoons and inter-monsoons over the years was carried out. It focuses on the variability and trends of each season. In this analysis, rainfall data were categorized into monsoons affecting Sri Lanka as the South West, East, and Inter-Monsoon One and Two. The first inter-monsoon rainfall is shown using the data from March and April in the last 10 years. The highest rainfall at the Maliboda (Dam) station is shown as 800mm in 2019. Regarding the change in rainfall patterns over time at various stations, the Hanwella station showed significantly higher rainfall in 2018 compared to other stations. The years 2020 and 2021 showed high rainfall on average. The bar graph in Figure 2 depicts the Northeast Monsoon rainfall from December to February. Rathnapura received the highest rainfall in 2014 and recorded 600 mm. Also, in 2020, the station received a significant rainfall of 550mm. Colombo and Hanwella stations show a general increasing trend in rainfall from 2017 to 2023. The temporal distribution of annual rainfall revealed marked internal fluctuation rather than a long-term trend. The lowest annual accumulation was recorded in 2016, with all stations receiving less than 200mm of precipitation. While the annual total increased, interannual variance showed no clear directional trajectory. The data for the months from June to September have been used. Compared to other stations, Maliboda station shows high rainfall, and it shows a maximum value of more than 900mm in 2020. Also, Rathnapura has received significant rainfall in 2016 and 2023. However, after the year 2020, there was a significant decrease at the Maliboda station. In the year 2022, there was no rainfall trend for the Angoda and Colombo stations. In 2023, more than 600mm of rainfall was received at Rathnapura station, which is recorded as the highest rainfall of that year. This also does not show a clear trend.



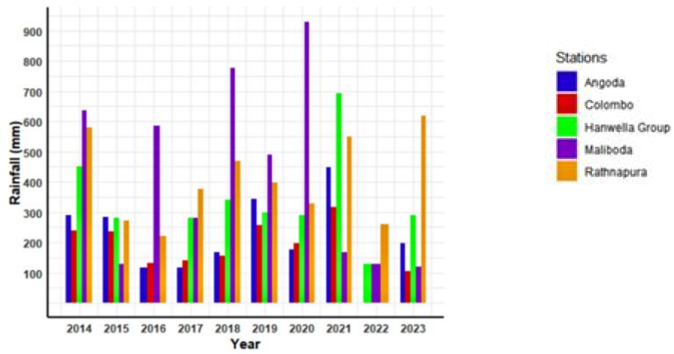
(a) First inter-monsoon season trend analysis of rainfall



(b) Northeast monsoon season trend analysis of rainfall



(c) Second Inter-monsoon season trend analysis of rainfall



(d) Southwest monsoon season trend analysis of rainfall

Figure 2. (a) First inter-monsoon season trend analysis of rainfall, (b) Northeast monsoon season trend analysis of rainfall, (c) Second Inter-monsoon season trend analysis of rainfall, and (d) Southwest monsoon season trend analysis of rainfall.

3.2. Temperature analysis in the Kelani River Flood Plain

The annual mean temperature trends at two major meteorological data collection centers, Colombo and Rathnapura, over 10 years from 2014 to 2023. Here, the x-axis represents 10 years of data. The y-axis represents the alcohol temperature in Celsius. The mean temperature trends of each station are represented by red-orange colour for Colombo and blue-green colour for Rathnapura. Temperature fluctuations are visible at both stations and show year-to-year variability. Colombo has an average temperature of 28.5°C with a peak in 2016. The average temperature for Colombo is between 28.0 and 28.7 degrees Celsius, while the temperature in Rathnapura is between 27.6 and 29.3 degrees Celsius. While temperatures in Colombo remain relatively stable, Rathnapura experiences large variations, with anomalous peaks, particularly in 2020. The horizontal dashed lines indicate the average temperature for each station. Neither of these stations shows a significant increasing or decreasing trend. According to the trend line, the temperature in Colombo fluctuates around a relatively stable mean. Although 2017 showed some peaks, it reflects no significant long-term trend. Also, at Rathnapura station as a whole, the trend stabilizes.

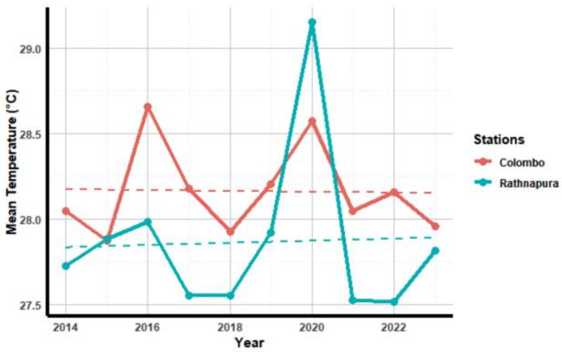
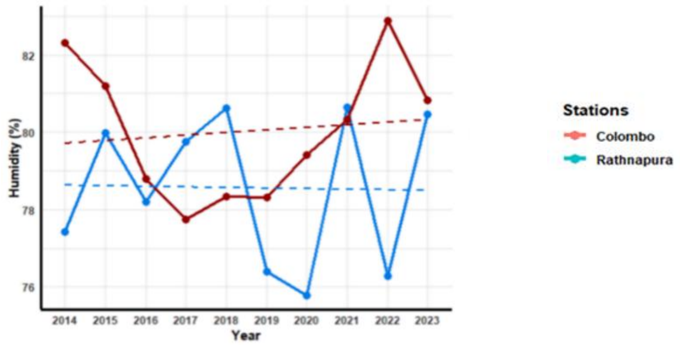
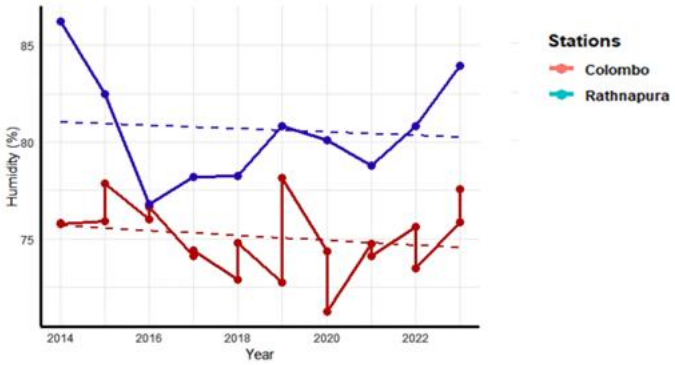


Figure 3. Annual Mean Temperature trend analysis

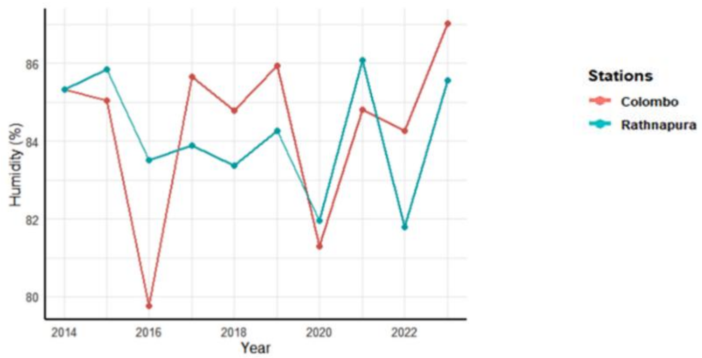
Based on Figure 3, the average humidity at Colombo station is around 81%, with a slight decrease from 2014 to 2016, followed by a significant decrease to the lowest point in 2016. The humidity gradually increases until 2018, then decreases until 2020. A significant increase occurred in 2022, reaching the highest humidity of the period. The average humidity at Colombo station is about 81%. Rathnapura station shows a gradual decrease from 2014 to 2016, then a steady increase until 2018. There will be a gradual decrease until 2020, followed by a significant increase until 2022, when the highest humidity levels are reached. The average humidity in Rathnapura is around 84%. Colombo station experiences more pronounced fluctuations. The humidity trend for Colombo shows a fluctuating pattern over ten years, starting at around 85% in 2014, dropping sharply to around 80% in 2016, then gradually recovering to a maximum in 2019, and showing a further decline around 2020. In recent years, especially in 2023, there has been a sharp increase in humidity levels, to more than 86%. Colombo station shows a generally stable pattern during the observed period, with humidity levels fluctuating around 82%, starting at around 82% in 2014. Humidity remains constant between 81% and 83% throughout the period, with no major peaks or troughs. A slight upward trend can be observed in 2016 and 2017, showing a high value of approximately 84%. The comparison of the two stations shows the difference in humidity behavior during the Southwest Monsoon (SWM). On the other hand, the Colombo station maintains a more stable and stable humidity level during the observed period. Rathnapura station shows a slight decrease in humidity level, while Colombo station is relatively stable (Figure 4).



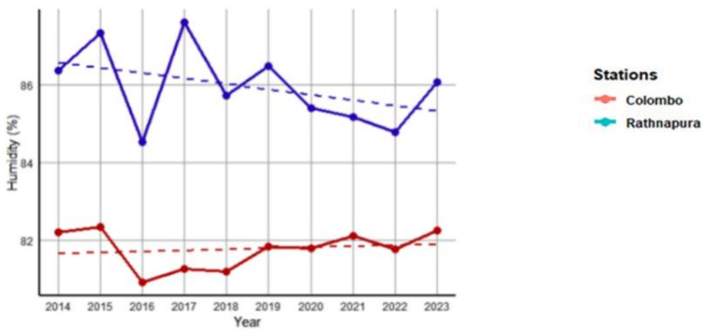
(a) First inter-monsoon (FIM) season trend analysis of humidity



(b) Northeast monsoon (NEM) season trend analysis of humidity



(c) Second Inter-monsoon season (SIM) trend analysis of humidity

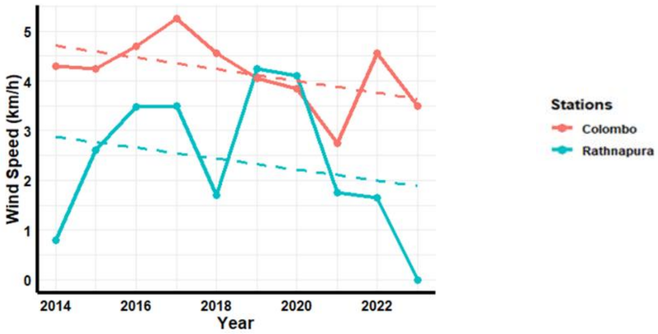


(d) Southwest-monsoon (SWM) season trend analysis of humidity

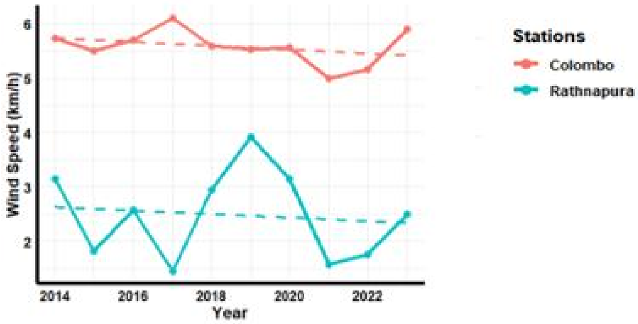
Figure 4. (a) First inter-monsoon (FIM) season trend analysis of humidity, (b)Northeast-monsoon (NEM) season trend analysis of humidity, (c) Second Inter-monsoon season (SIM) trend analysis of humidity, and (d) Southwest-monsoon (SWM) season trend analysis of humidity.

3.3. Wind Speed Data Analysis in the Kelani River Flood Plain

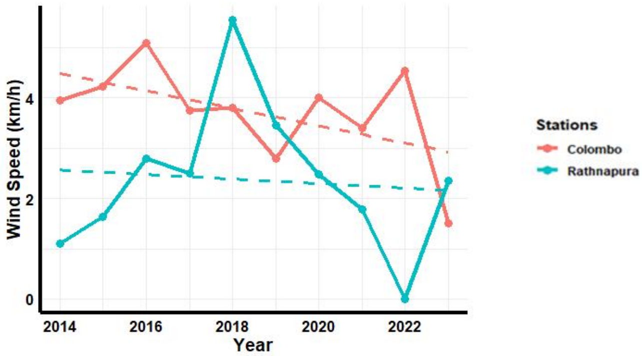
The trend depiction of wind speed during the first inter-monsoon period from 2014 to 2022, comparing Colombo station and Rathnapura station. Wind speed at Colombo station shows an overall fluctuating pattern with a mild upward trend. The wind speed in 2017 shows the maximum, which is higher than 5 km/h. In 2021, the wind speed shows a slight decline, but by 2022, it remains close to 5 km/h. Wind speed at Rathnapura station also fluctuates but remains relatively stable, with values mostly around 4km/h. There is a slight decrease, especially towards the end of the period in 2022. Rathnapura Station shows more variability, starting at more than 3km/h in 2014, with prominent peaks and troughs throughout the year. Wind speed at Rathnapura Station exhibits significant variability and a downward trend, with a significant decrease after 2020. It then fluctuates between 2017 and 2022, where it remains around 3.5 km/h. The wind speed rapidly increased, reaching 5 km/h, the highest wind speed recorded for this location during that period. This line graph depicts the trend of wind speed at the two stations, Colombo and Rathnapura, during the southwest monsoon from 2014 to 2023. Wind speed at Colombo station shows moderate fluctuations but maintains a relatively stable level with a slight downward trend over time. The highest wind speed was around 6.3 km/h in 2016. After 2016, wind speed shows a gradually decreasing trend, with fluctuations of about 5 km/h between 2017 and 2022. By the year 2023, wind speed will stabilize at around 5.2 km/h, showing a slight increase from its decline in previous years. Indicating a steady decrease in wind speed during the southwest monsoon and during NEM, the trends of wind speed in both Colombo and Rathnapura stations showed an overall decrease, but the rate of decrease in Rathnapura station was more severe. Based on the Penman-Monteith potential evapotranspiration (PET) equation (Tegos et al., 2015), a decline in wind speed reduces PET, which slightly increases residual soil moisture retention. Based on this contribution to higher net catchment runoff during subsequent high-rainfall events (Figure 5).



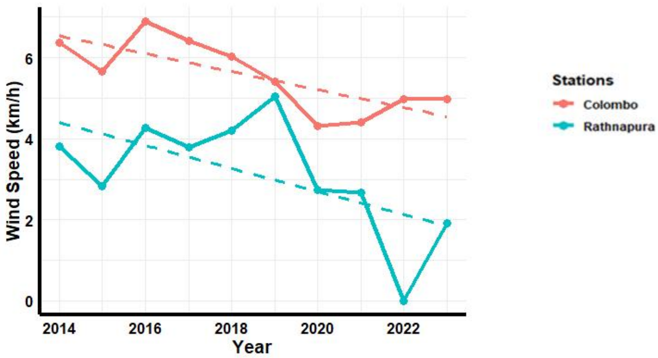
(a) First inter-monsoon season trend analysis of wind speed



(b) Northeast monsoon season trend analysis of wind speed



(c) Second Inter-monsoon season trend analysis of wind speed



(d) Southwest monsoon season trend analysis of wind speed

Figure 5. (a) First inter-monsoon season trend analysis of wind speed, (b) Northeast monsoon season trend analysis of wind speed, (c) Second Inter-monsoon season trend analysis of wind speed, and (d) Southwest monsoon season trend analysis of wind speed.

3.4. Mann- Kendal and Sen's Slope test results

The significance of this value lies in its comparison with a standard normal distribution (Z-score). A Z-score of this magnitude usually shows a significant trend. The p-value is 1.548e-12 (or 0.000000000001548), which is extremely low. The mean values indicate that the increasing precipitation trend is statistically significant, and there is no chance that the trend is due to random fluctuations. A Tau value of 0.4191 indicates a moderate positive correlation, which is consistent with the findings of a positive trend in the data set. Statistical significance was evaluated using non-parametric Mann-Kendall (MK) tests combined with Sen's Slope Estimator in RStudio. A standard significance threshold of $\alpha = 0.05$ (95% confidence level, $p < 0.05$) was adopted to determine statistically significant positive or negative trends (Pielke et al., 2011; Belvederesi et al., 2022). Based on the Mann-Kendall trend test, it can be concluded that the rainfall data show a statistically significant upward trend. Although a rate of 3.12 mm/year may seem normal, over several decades, it can lead to a significant increase in annual rainfall. Recent studies align with these results (Alahacoon and Edirisinghe, 2021; Samarasinghe et al., 2022), which reported localized increases in extreme monsoon rainfall in the western wet zone of Sri Lanka.

The table shows the trends for four specific periods: FIM, NEM, SIM, and SWM. Angoda station does not show significant trends in FIM, NEM, or SIM but shows an increasing trend during SWM. The rainfall suggests an increase except during the SWM period. Rathnapura station shows an increasing trend in FIM, SIM, and SWM and no trend in NEM, indicating increasing rainfall in most seasons. Accordingly, since the absolute value is quite small, this trend is not strong. The p-value of 0.72051 is significantly higher than significance levels (e.g., 0.05 or 0.01). Accordingly, the test wasn't significant trend in the temperature data over the 10 years. A low value of S indicates that only a weak trend is observed, which means that there is a limited number of significant differences across the data set. This indicates that the average humidity at the beginning of the study period was approximately 82.5%. A slope of -0.1 means that for every unit increase in the independent variable, humidity decreases by 0.1 unit. The Mann-Kendall test shows that the Tau value is -0.270, suggesting a moderate negative trend in wind speed over the period analysed. The initial value of the wind speed at the beginning of the disturbance analysis period of 273 is approximately 273 km / h. Since the slope is negative, it implies that the wind speed has decreased during the observed period. For each unit increase in the independent variable, the wind speed is expected to decrease by an average of 0.134 units each year. Although this relationship shows a trend, it is not conclusive enough.

3.5. Hydrological Model

Based on Figure 6, the x-axis of this scatter diagram shows the actual observed flow (m^3) of the river, which serves as a critical indicator for flood risk analysis (Montgomery et al., 2021). Axis Y represents the expected flow (m^3), calculated using the hydraulic model under current scenarios of climate and land use. This is especially important for low-water conditions of low water, which are of decisive importance for the assessment of low-water conditions and are often affected by droughts caused by climate change or precipitation character changes (Trenberth, 2005). The points usually do not coincide with the trend line. Low correlation for downstream flows and the scattered nature of the points at low streamflow values (around 40 m^3) highlight a weak correlation between actual and predicted flows 2 (Belvederesi et al., 2022). Based on the specific data at 40 m^3, there are significant deviations. They may reflect extreme local conditions, such as heavy rains or sudden changes in land use, which the model may not fully reflect (Pielke et al., 2011)

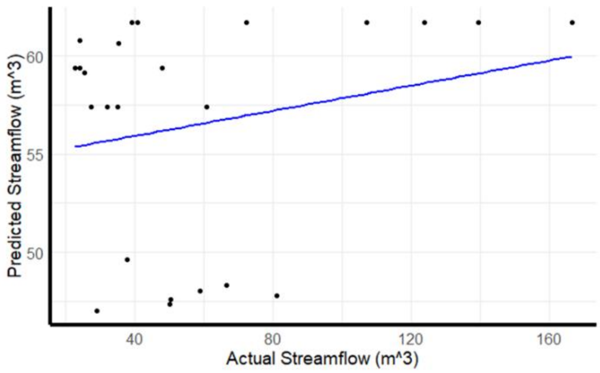


Figure 6. Actual vs. predicted streamflow daily data

Proper calibration to incorporate climate variability and flood changes (e.g., vegetation recovery) (Brunner et al., 2021) is needed to improve predictions under future conditions. Recalibration of the model to better capture observed flow patterns is especially important during periods of low flow, which is important for assessing the impact of climate conditions on river hydrology (Huang et al., 2020). The residual versus fitted diagnostic plot (Figure 7) highlights the operation of the baseline hydraulic model across varying flow patterns. Recalibration of the model to better capture observed flow patterns is especially important during periods of low flow, which is important for assessing the impact of climate conditions on river hydrology. (Huang et al., 2020). Residuals exhibited significant variation and ranged from 50 to 200, indicating heteroscedastic conditions during peak and low flows. This non-random pattern suggests that standard linear regression hydraulic modelling will not capture non-linear hydrological responses and rapid catchment dynamics during extreme weather events (Brunner et al., 2021; Dilling et al., 2015). The evidence justifies the development of dedication high flow and low-flow frameworks in future studies. Specifically, future work should prioritize recalibrating and updating the model using non–linear algorithms (e.g., machine learning or dynamic hydrologic solvers) tailored specifically for extreme runoff events.

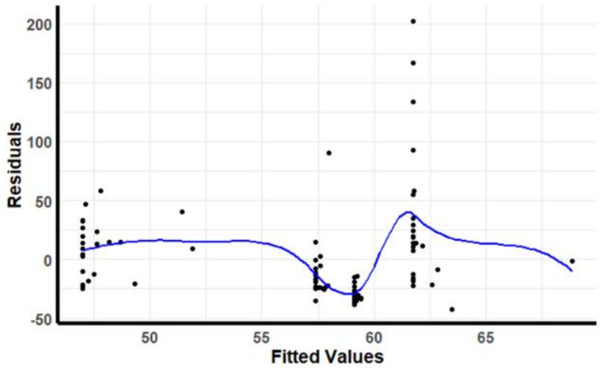


Figure 7. Q-Q (Quantile-Quantile) Plot of Residuals

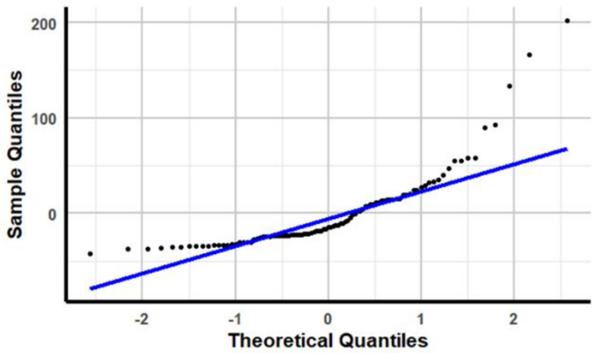


Figure 8. Q-Q (Quantile-Quantile) Plot of Residuals

Figures 7 and 8 explain that the irregular nature of the blue lines indicates that the model does not fully account for the complex hydrological changes caused by climate change (Gleick, 1986). The observed waves in the residuals indicate that high variability in precipitation or changes in soil moisture are both missing important environmental factors in the model, such as tidal estimates. As the installed value increases, the residual amount increases. This indicates that model performance degrades during high-flow events. This behavior may be related to the inability of the model to determine the full flood. The ability to predict these high-flow conditions is therefore essential (Wang et al., 2011). The existence of heteroscedasticity reflects the need to adjust the model to improve its performance under flood conditions. Some residual values exceed 100, indicating potential outliers in the data. The model severely underestimates the actual data flow. Exploring more complex nonlinear models can better predict upstream and downstream flows needed for flood recovery planning. Incorporating those variables into this hydraulic model can provide more accurate predictions of future flows under different climates and help plan and improve floodplain restoration efforts to ensure their long-term sustainability (Kiedrzyńska et al., 2015). Sri Lankan hydraulic models are often used to simulate the flow of water and guide adaptation measures. Simulations make it easier to predict future flows (Giorgi and Mearns, 1991), especially under changing climates. The curve at the top right of the graph represents the upper end, which means that the model produces many positive residuals (Samadi et al., 2018).

These are outliers that estimate actual runoff. In the context of climate change dynamics, these dynamics may respond. This indicates that the model sometimes overestimates the event flow, but this is less of a problem than underestimating the event flow. Based on Figure 8, the model struggles to describe the extreme runoff (Nilsen and Gottschalk, 2011). Events that are crucial to predicting the impacts of climate change, due to the increase in frequency, and models that underestimate the severity of extreme weather events, such as excess rainfall and flash flooding, may lead to inadequate preparedness and mitigation measures. Significant deviations from a normal distribution indicate that the current hydraulic model is detailed (Domeneghetti et al., 2012), meaning that the model does not relate to the specific physical processes that drive streamflow under conditions in extreme cases. This provides normalized effects and better captures relationships between variables, improving the model's ability to predict extreme events, a condition essential for predicting the effects of climate (Meehl et al., 2000). Depending on the accuracy of hydraulic models in predicting future flood conditions, given the observed problems with the model's accuracy in predicting extreme events, inconsistency (Hapuarachchi et al., 2011). This awareness can help design more adaptive restoration strategies, such as integrating green infrastructure and natural catchment systems, which may be more effective under different flood conditions

Based on Figures 9 and 10, the Hydraulic models provide valuable information on floodplain dynamics under different climate change scenarios by incorporating projections of increased rainfall and higher temperatures into these models (Chomba et al., 2021). This allows planners to predict potential flood risks and evaluate the success of restoration strategies (Ginige et al., 2022). The Kelani River may fail to reduce the risk of flooding, resulting in increased risk to local communities. The evaluation of the impact of each data point on the overall model, larger trigger points indicate that the data disproportionately influence the model's predictions in hydraulic modelling (Gori et al., 2019). High breakpoints often represent extreme events such as major floods or severe droughts. These influencing factors must be carefully considered during the calibration process. High impacts resulting from climate change and urban development should be carefully considered in regeneration planning (Carter et al., 2015). If these events are properly considered, the effectiveness of the proposed reform strategy will increase significantly. Integrating climate change projections into hydraulic models ensures that flood recovery is predictable and resilient, as currents are already showing in Sri Lanka.

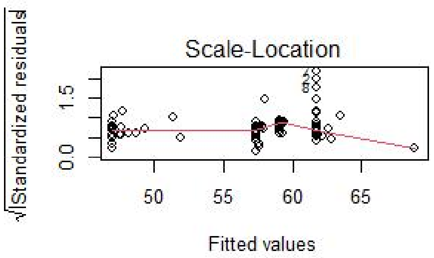


Figure 9. Scale Location Plot

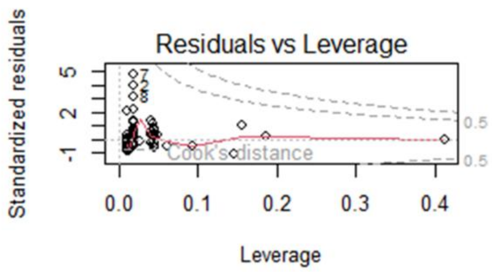


Figure 10. Scale Location Plot

Flood restoration in Kelani is expected to reduce flood risk and improve ecosystems. Hydrologic modelling provides insight into how different restoration strategies influence flood risk and ecosystem restoration in Kelani; for example, modelling with wetland restoration (Manawadu and Wijeratne, 2021). Floodplains are crucial natural habitats for various animal species, contributing to biodiversity and ecosystem restoration (Surasinghe et al., 2019). Strategies such as afforestation, wetland restoration, and removal of obstructions to natural water flow can significantly reduce flooding risk during the monsoon season (Liyanage et al., 2024). Riparian afforestation improves riverbank stabilization, reducing downstream velocity and limiting the extent of flooding. Other flood strategies, such as levees or green infrastructure, may need to be supplemented with more comprehensive rehabilitation plans to ensure flood alleviation at the local level (Wu et al., 2021). The hydraulic modelling supports natural floodplain restoration as an effective measure to reduce flooding conditions and improve ecosystem services (Figure 11).

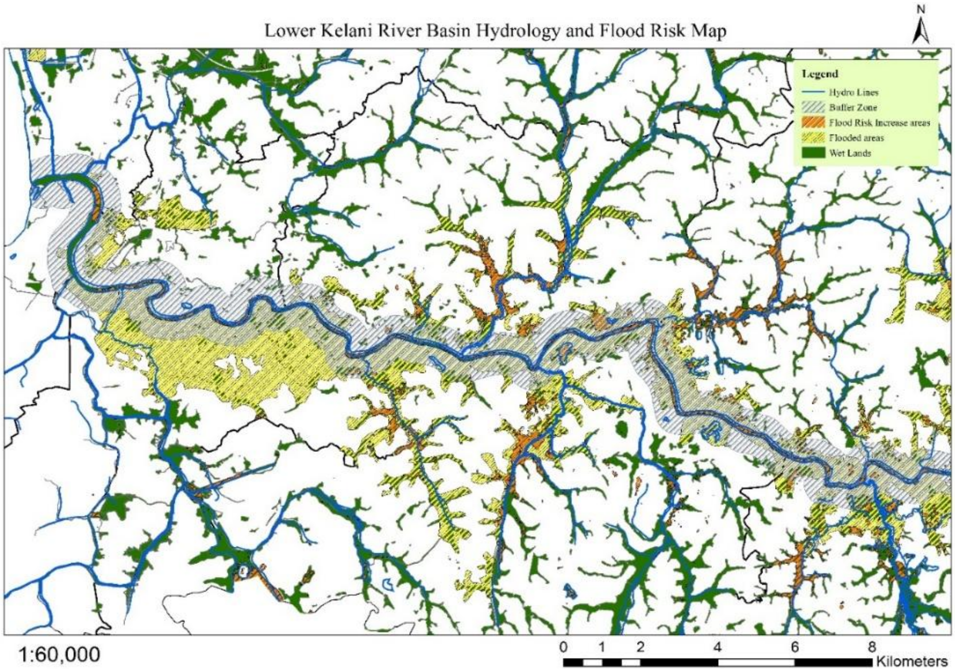


Figure 11. Lower Kelani River Basin Hydrology and flood risk map

3.6. Policy Recommendations and Scope for Future Research

Implementing these strategies in Sri Lanka presents challenges such as financial constraints, competing demands for land use, and community resistance due to limited awareness of the benefits of reforms (Madsen et al., 2014). Broader implications for water management suggest that resilience strategies such as natural watershed restoration can improve resilience, enhance water carrying capacity, and adapt critical ecosystem services such as biodiversity and flood mitigation (Lawler et al., 2013). Integrating floodplain restoration with floodplain management ensures a holistic approach that promotes long-term sustainability, climate resilience, and protection of vulnerable communities in the Kelani Basin.

The findings are presented in the development of policy for KRB. The proposed framework directly supports the statutory provisions of the Sri Lanka Flood Protection Ordinance (No 4 of 1924) (Thilakarathna, 2019). The ordinance mandates directional irrigation, delineates flood plains, and formulate protection scheme, and incorporates model and machine learning methods into the legal pipelines, enabling dynamic mapping and precision peak discharge estimation modernization the statutory flood area declaration process in (Section.3). Integrating nature-based solutions such as natural watershed and floodplain restoration into the ordinance's legal scheme provides statutory backing for land use zoning and drainage management regulation (Section 9) (Thilakarathna, 2019). This bridges the gap between high-resolution predictive modelling and an enforceable flood protection scheme across the KRB. Additionally, using higher-resolution images, such as LiDAR-derived DEM and real-time observations, will improve peak discharge estimation. Combining these outputs can prepare a multi-criteria socio-economic decision-making process aligned with flood risk management across vulnerable communities in Sri Lanka. Future studies should focus on integrating a hybrid modeling framework that combines physical based hydraulic model with advanced machine learning algorithms. Such as Random Forest, Long Short-Term Memory (LSTM), and Extreme Gradient Boosting (XGBoost), to enhance real-time flood forecasting and minimize hydrological prediction error (Lawler et al., 2013).

4. Conclusion

Climate change impact assessment and hydrological modelling of the lower Kelani River basin indicate significant changes in rainfall and runoff. This is especially true at stations like Rathnapura and Maliboda, where rainfall is highly variable. The ocean temperature pattern is relatively stable, while Rathnapura is more volatile. Different climate effects are highlighted in other regions. The humidity shows a slight increase, although the trend is stable, and the wind speed at Colombo station shows a decreasing trend. Rathnapura station shows more variability. The hydraulic model developed in this study has shown good performance in predicting high flows, while low flow conditions are difficult to determine. The scatter plot of actual flow versus predicted flow shows that the model overestimates low flows and underestimates high flows. An important tool for flood risk assessment and planning flood recovery measures.

Author Contributions

For research articles, L.A.W.A.C Liyanage and N.A.R.B Samaranayake contributed equally to all aspects of the study, including conceptualization, methodology, analysis, and manuscript preparation. All authors have read and approved the final version of the manuscript.

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Conflict Of Interest Statement

No conflicts of interest.

Data Availability Statement

The data used in this study will be made available upon request.

Reference

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